

Increasing Object-Level Reconstruction Quality in Single-Image 3D Scene Reconstruction

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Abstract

1. Introduction

While humans can easily infer the 3D structure as well as the complete (panoptic) semantics of a scene from a single image, this task has been a longstanding challenge in the field of computer vision. The task fundamentally prerequisites learning a strong prior of the 3D world. Traditional methods have made significant strides, from generating geometrically coherent structures [9, 31] to learning different instance semantics [13, 20, 29]. More recent approaches directly learn the 3D panoptic semantics as a whole [7, 40], yet they fall short in capturing the intricate details and nuances at the object level. This paper introduces a novel approach to bridge this gap by integrating a specialized object-level model into the reconstruction process, thereby leveraging the specialized model’s object-priors.

Our approach models panoptic 3D reconstruction as a two-stage problem. We first use the model of Dahnert et al. [7] to create an initial reconstruction. Then, we leverage the instance masks to extract the object geometries out of the reconstructed scene. We input each of the extracted objects along with cropped images from the scene and text labels into a diffusion model [5] to refine the rough object-level geometries. Finally, we integrate the refined object geometries back into the initial scene reconstruction to obtain a complete and refined panoptic 3D scene reconstruction.

In summary, our main contributions are as follows:

- We propose a novel approach to panoptic 3D reconstruction involving an inference pipeline that leverages object-level reconstruction models to refine the output of a 3D scene reconstruction backbone.
- We qualitatively demonstrate the effectiveness of our approach on the 3D-Front [11] dataset, showing significant improvements over the state-of-the-art.
- We show that fine-tuning SDFusion [5] on the input scene’s object distribution (in our case the 3D-Future

dataset [12]) significantly improves the quality of the re-fined objects.

- We propose *weighted masking*, a novel technique to integrate masking uncertainty into the object-level reconstruction process.
- We introduce a conceptually simple yet effective method for shape alignment, which outperforms rigid alignment methods in our experiments.
- We openly release our model code, training and inference pipelines, as well as our newly constructed variation of the 3D-Front dataset to facilitate future research in the field.

2. Related Work

2D panoptic segmentation 2D panoptic segmentation merges semantic and instance segmentation, providing detailed pixel-level parsing of images, capturing both general categories (semantic segmentation) and individual object identities (instance segmentation) [18]. Since the original task formulation by Kirillov et al. [18], a number of works have been proposed to solve the task [2–4, 19, 21–23, 28, 33, 34, 37–39], while more recent approaches [17] try to unify image segmentation in its entirety.

Single-view 3D reconstruction The work by Snavely et al. [32] was the first notable attempt at reconstructing 3D scenes from unordered photo collections. Since then, the field of image-based 3D reconstruction has seen a number of advancements, culminating in the task of single-view 3D reconstruction [6, 9, 16, 26, 29, 31, 35].

Shape priors Wu et al. [36] note that the task of single-view 3D reconstruction is non-deterministic, as there are many 3D shapes that can explain a given single-view input, and propose to use shape priors to shape the solution space such that the reconstructed shapes are realistic, but not necessarily the ground truth.

3D scene understanding The task of 3D scene understanding and panoptic reconstruction is analogous to its 2D

counterpart and aims to infer the 3D structure and semantics of a scene, including the 3D layout, object instances, and their 3D shapes from images [7] or noisy geometry [14, 15]. Dahnert et al. [7] propose a method – henceforth called *Panoptic 3D* – to jointly solve the tasks of 3D scene understanding and single-view 3D reconstruction by lifting features produced by a 2D backbone into a 3D volume of the camera frustum, and jointly optimizing for geometric reconstruction as well as semantic and instance segmentation.

Modality-conditioned shape generation 3D generative models represent objects in a variety of modalities, including point clouds [1, 25], occupancy grids [26], meshes [27], and signed distance functions [30]. Furthermore, these models can also be distinguished by the type of input they take, such as incomplete shapes [8], images [10], text [24, 41], or other modalities [42]. Notably, Cheng et al. [5] propose *SDFusion*, a 3D object reconstruction method conditioned on images, text and geometrical input.

Datasets Research in 3D panoptic reconstruction relies heavily on datasets to train and evaluate algorithms. Notable datasets in this domain include ScanNet (cite here) and Replica (cite here), which provide rich annotations for scene understanding tasks.

Among these datasets, the 3D Front dataset stands out for its comprehensive coverage of indoor scenes. Created by Li et al. (cite here), 3D Front offers detailed geometric reconstructions, semantic segmentation, and instance segmentation annotations for various indoor environments, including living rooms, kitchens, and bedrooms. The synthetic 3D dataset contains 6,801 mid-size apartments with 18,797 rooms populated by 3D shapes from the 3D-Future (cite here) dataset. The dataset’s high-quality data acquisition process ensures accurate representations, making it a valuable resource for advancing research in 3D panoptic reconstruction.

3. Method

Given a 2D RGB image, we leverage Panoptic [1] to predict the geometry within the camera frustum of the image, as well as the corresponding 3D semantic- and instance labels. Since panoptic already predicts instances in 2D and uses this as a prior for 3D instance segmentation, we have access to both 2D and 3D instances. We use the 2D instance mask to crop out an RGB image of the detected object and the 3D instance mask to crop out the reconstructed object shape. Then we input the 3D shape, the 2D cropped image and the semantic label (as text) into the *SDFusion* model.

The *SDFusion* model uses task specific encoder to encode the conditions (the 2D image and the text) and separately brings the 3D shape into the latent space, in which it applies

the latent diffusion process. After applying noise to the latent code, the condition embeddings are concatenated and cross-attended to in the denoising network, in order to modulate the diffusion process. A decoder then reconstructs the shape. The output of *SDFusion* is front-facing and potentially not matching the orientation of the object in the reconstructed 3D scene. Therefore we employ a registration algorithm to align the reconstructed objects back into the scene.

Panoptic 3D Scene Reconstruction Panoptic [1] takes a single RGB image and reconstructs geometry and predicts semantic- and instance segmentation for the corresponding geometry. Panoptic employs a ResNet-18 encoder to compute features of an RGB image. These features are used to predict both a 2D depth map and 2D instance masks using a depth decoder and Mask R-CNN on the ResNet-18 output. The depth map is used to backproject the features into a sparse volumetric grid and the 2D instance mask is propagated to serve as a seed for the 3D instance mask prediction. A U-Net architecture takes the sparse backprojection to predict occupancy, distance field, semantic- and instance labels for each occupancy.

SDFusion *SDFusion* [2] takes a signed distance field as main input and takes an RGB image as well as a text as input to condition the main input on. A variational autoencoder compresses the signed distance field into a latent space representation. Within the latent space, a diffusion process is employed which gradually diffuses the latent code. Before denoising, the conditions are encoded and concatenated to the noisy latent code. Then, a 3D UNet is used to denoise the latent code and an attention mechanism is used to allow the denoising network to attend to the conditions during denoising. The reconstructed latent code is then decoded using the decoder of the variational autoencoder. The result is a reconstructed signed distance field.

Registration For the registration we use a method that aligns the reconstructed front-facing *SDFusion* output. We first align the reconstructed output to the floor in our 3D scene and then rotate in 16 different, uniform positions around its y-axis. We select the orientation which leads to the smallest per-point difference.

4. Conclusion

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